



Robust Decision Making: The Cognitive and Computational Modeling of Team Problem Solving for Decision Making under Complex and Dynamic Conditions

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**Final Report: The Cognitive and Computational Modeling of Team Problem
Solving for Decision Making Under Complex and Dynamic Conditions**

Jonathan Cagan and Kenneth Kotovsky

Carnegie Mellon University

Grant no: FA9550-12-1-0374

ABSTRACT

The focus of this work is to understand impactful aspects of team functioning as they solve complex problems, and propose the means to improve the performance of teams, under changing or adversarial conditions.

By analyzing the characteristic differences between high performing and low performing teams, we identified behavior that characterized and differentiated the problem solving approach of the teams especially when the problem itself changes during solving. We then derived a simulated annealing-based algorithm that mimicked human team problem solving under these conditions; aspects of the algorithm also performed well as an optimization algorithm when solving a variety of hard numerical problems.

Identification of the impact of team structure on problem solving behavior under changing conditions indicates that heterogeneous-grouped teams outperform homogeneous or non-grouped teams. Yet solving multiple problems sequentially is not as effective as breaking problems into smaller intermixed chunks, breaking fixation.

Finally, a meta-analysis on the design literature where the impact of examples on problem solving was studied within the design process identified under what conditions examples will induce fixation or alternatively, inspiration.

STUDY 1: Effect of Team Structure on Problem Solving Under Change (Sio, Kotovsky and Cagan, 2014b)

In this study, we conducted an experiment and computational simulations to look at how team structure affects the information processing within a diverse team, and how this affects team performance and resilience to change.

Experiment: 120 participants were assigned in teams of four to make decisions in which they were given performance data and had to evaluate some companies and pick the best one. Two members of each team were told to evaluate the companies based on *company performance*, and the other two were told to focus on *industry trends*. Teams were in different subgrouping structures: *homogeneous*, *heterogeneous*, and *no-subgrouping*. In a *homogeneous* team, members studying the same domain of information formed a subgroup to evaluate the companies together. The entire team then had a discussion and made a decision on the best company. The *heterogeneous* teams followed a similar procedure except that each subgroup was mixed, including one member from each orientation. Members in the *no-subgrouping* teams evaluated the companies alone, followed by a team discussion. There were 20 trials. *Industry trends* were driving the correct decision for the first 10 trials. From trial 11 to 20, a significant change was introduced; *company performance* became the most important factor. Teams were not informed of the change, only whether their choice was correct.

The expectation was that members in the homogeneous subgroup would validate each other's perspective because of the high functional similarity between them. Thus, they should be fixated on their own preference, making them less able to combine different perspectives in decision-making and adapt to the change. The 20 trials were divided into 4 equal blocks, representing the early and late trials, presented before and after the change, for comparison purposes. As predicted, the homogeneous team performed significantly worse than the no-subgrouping and heterogeneous teams in the 1st block, suggesting that the homogeneous team was slower in learning the task. Further, all teams were impaired by the change to the same degree, indicated by the non-significant team performance difference in the 3rd block. The performance difference re-emerged in the 4th block where the homogeneous team performed worse than the other two teams, suggesting that the homogeneous team was less able to adapt to the change (see Figure 1). This can be viewed as a form of fixation.

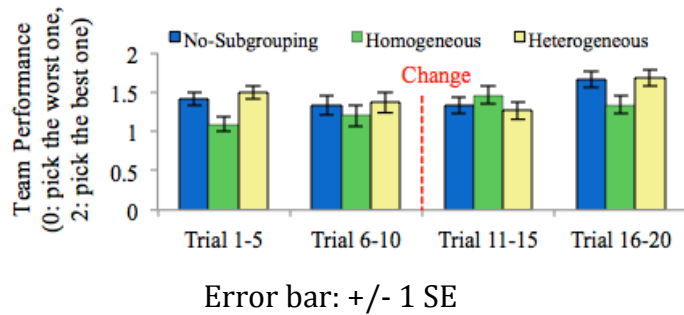


FIGURE 1. Team performance by block and team structure.

Computational Modeling: Three 3-layer (an input, a hidden layer, and an output) neural network models (see Figure 2) were built to simulate the results of each condition of the experiment. Each input node received the evaluation by one member as input, and forwarded it to the hidden nodes. The three models differed in the interconnectivity between the input and hidden layers, representing the homogeneous, heterogeneous, and no-subgrouping structures. To simulate the communication patterns of the team discussion, the hidden nodes were fully-connected with each other allowing them to inhibit or excite each other.

Models were first trained on the pre-change training set for 200 cycles, and then on the post-change set for another 200 cycles. Figure 3 presents the performance (number of errors) of the models when learning the pre- and post-change trials. At the beginning, the heterogeneous and no-subgrouping models demonstrated a steeper decline in errors than the homogeneous model. The differences then diminished over time. All models were impaired by the criteria change in the training set of data, indicated by the significant increase in error immediately after the change. All models demonstrated a decrease in error after the first few cycles of training. But the homogeneous model ceased to improve after that. Only the heterogeneous and no-subgrouping models continued to improve, showing a rapid and effective response to the changed conditions.

The results of these experimental and computational studies demonstrate a sizable impact of team communication structure and representational convergence on a team's ability to avoid fixation and respond to changed situations.

This work is accepted for publication in *CogSci 2014* (Sio, et al., 2014).

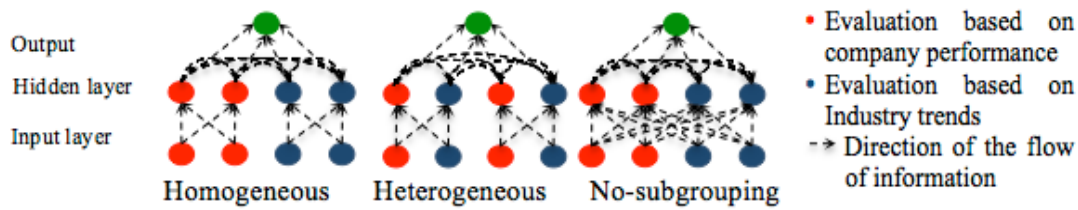


FIGURE 2. The architecture of the models.

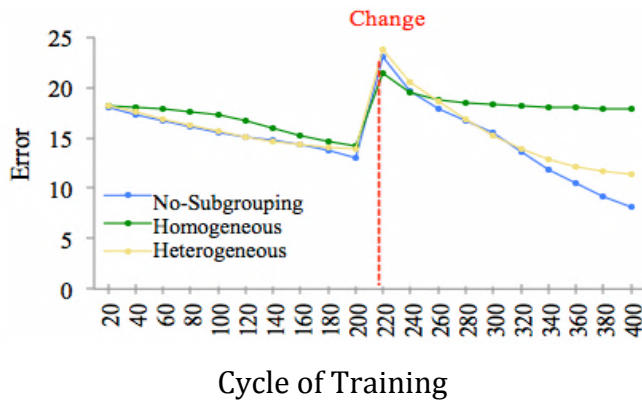


FIGURE 3. Computational model performance

STUDY 2: Strategy Characteristics of High vs. Low Performing Teams in responding to sudden changes in problem conditions. (McComb, Cagan and Kotovsky, 2014 & 2015a),

Differences in problem-solving processes could result from the inherent variability of the individuals composing the team, where individual-level domain experience could lead some individuals to perform more like experts than others, inducing team-level differences. This led us to hypothesize that *teams that excelled in responding to change would display underlying problem-solving processes that differed from teams that responded slowly or poorly.*

We explored this hypothesis through a cognitive study that tasked small teams of undergraduate engineering students with the design of a truss structure. Midway through the study, a fundamental aspect of the original design problem was changed. Shortly thereafter, yet another modification was made to the original design problem. The second change was intended to amplify the differences between high- and low-performing teams

by placing an emphasis on ongoing flexibility and responsiveness. During solving, a complete record of the design team's efforts was collected through a computer interface, designed to allow problem-solving strategies to be fully reconstructed for analysis. Upon reconstruction, individual designs were analyzed in terms of quality. We quantified quality using the strength-to-weight ratio (SWR), normalized according to the objectives given to the teams. The level of divergence exhibited by teams was also analyzed. This was quantified by computing the average pairwise distance between designs being pursued by all pairs of members of a team during the entire solution process.

To compare the high- and low-performing teams, teams were first sorted according to average performance. The five highest and five lowest performing teams were then selected for further analysis. The SWR of the best designs pursued by these teams are shown in Figure 4. There was a considerable difference in the SWR of the problem design solutions produced for the first problem statement and third (second change) problem statement, with a smaller difference exhibited for the second (first change) one. Further, high-performing teams also showed a pattern of divergence that was quite different from the low-performing teams. Figure 5 shows the average intra-team pairwise distance through the study. In general, low-performing teams continued to diverge, moving far from their previous solution. On the other hand, high-performing teams explored more focused portions of the design space. A more detailed examination of designs produced by the high- and low-performing teams indicated that high-performing teams tended to pursue simple designs, while low-performing teams pursued more complex but less efficacious designs (examples are provided in Figure 6).

The differences between high- and low-performing teams can be explained in part through cognitive load theory. Cognitive load theory states that the cognitive load associated with a task is composed of intrinsic load (difficulty of the task itself), extraneous load (additional load related to method of delivery), and germane load (load devoted to understanding information) (Kirschner, 2002). Through producing simple designs, the high-performing teams placed little extraneous cognitive load on themselves, which enabled them to better understand the design space. This augmented their ability to respond quickly to changes. Members in low-performing teams tended towards more complex designs, which inhibited this ability.

The concept of expertise can also be utilized to interpret the results. It has been demonstrated that problem-domain experts can quickly and accurately classify problems, and begin moving more or less directly towards a solution (Chi, Feltovich, & Glaser, 1981). Specifically in the context of design, expert designers tend to quickly commit to a single solution concept, rather than exploring a variety of alternatives (Cross, 2004). While true expertise is generally the result of years of effort, individuals in high-performing teams still behaved in some ways like experts, quickly selecting a good direction in which to search. In addition, they exhibited a low level of divergence, similar to the balanced search strategies observed in expert designers by Fricke (1996).

The general strategy that the high-performing teams used to solve the problem has been identified (a combination of exploring simple solutions, and limiting divergent search). For some problem-solving tasks, it may be beneficial to teach this strategy to teams in order to increase the likelihood of expert-like behavior. This work is accepted for publication in the ASME Design Theory and Methodology Conference (part of IDETC) in 2014 (McComb et al, 2014).

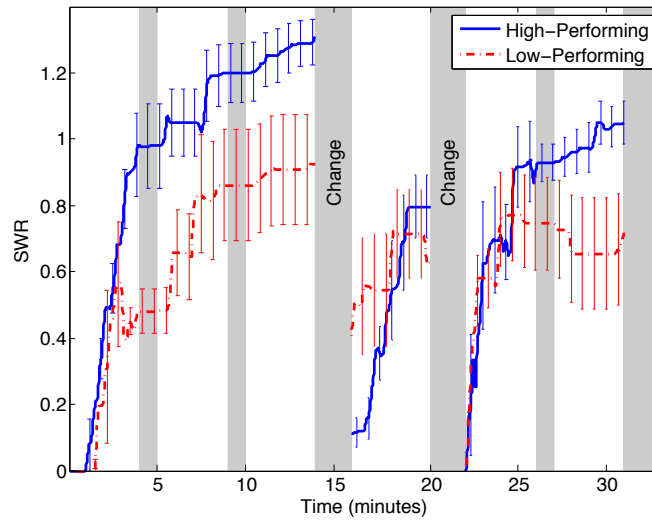


FIGURE 4. SWR (Strength-to-weight ratio) of best designs for high- and low-performing teams (error bars show ± 1 S.E)

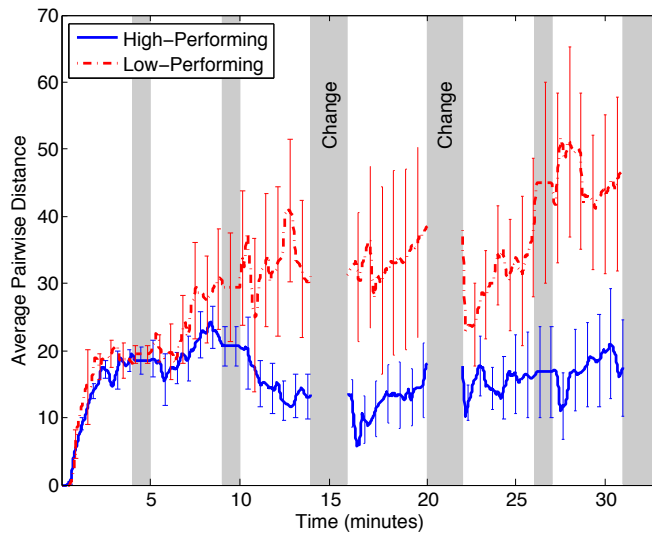


FIGURE 5. Average pairwise distance of high- and low-performing teams (Error bars show ± 1 S.E)

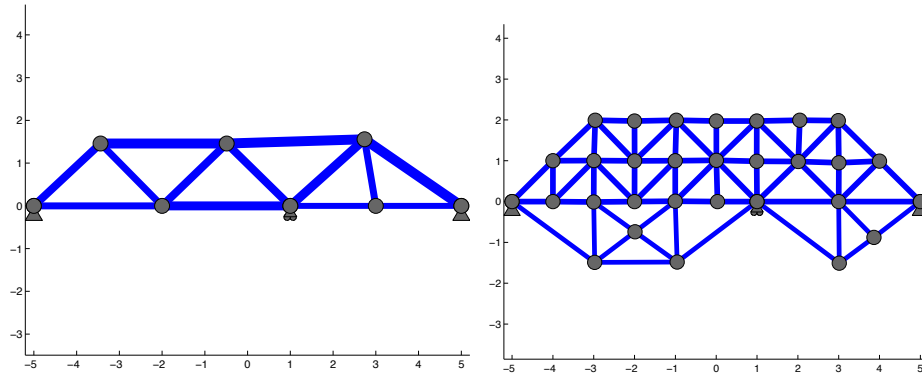


FIGURE 6. Representative solutions to the second problem statement for a high-performing team (left) and a low-performing team (right)

STUDY 3: Computational modeling of teams that exhibit high performing characteristics under dynamic conditions (McComb, Cagan and Kotovsky, 2015b & 2015e)

This work focuses on developing a better understanding of team-based design through computationally simulating the team design process by introducing a Cognitively-Inspired Simulated Annealing Teams (CISAT) modeling framework. The CISAT framework makes use of simulated annealing constructs to model several characteristics of individuals in small design teams. It differs from other simulation models because it strikes a balance between model simplicity and direct applicability, offering a succinct modeling framework that can be used to directly solve engineering design problems. Further the framework enables an analysis of which attributes of a solution strategy most impact the solution outcome.

The CISAT framework models 8 characteristics supported by the literature, including the results of Study 2 above, that contribute to a description of how individuals solve problems, both independently and as part of a team. These characteristics are listed briefly below, and explained in greater detail in subsequent sections:

1. **Multi-agency:** A team is a collection of individuals with a common goal.
2. **Organic interaction timing:** Interaction within teams occurs at irregular intervals.

3. **Quality-informed solution sharing:** Members of a team tend to focus on the most promising alternatives, but don't do so myopically.
4. **Quality bias reduction:** Individuals in a team develop multiple solution concepts to avoid premature convergence.
5. **Self-bias:** Designers tend to be biased in favor of their own designs.
6. **Operational learning:** Individuals learn strategies over the course of solving.
7. **Locally Sensitive Search:** Designers select from a range of breadth- and depth-first search strategies as they explore the design space.
8. **Satisficing:** Individuals only search the solution space until a solution is found that satisfies relevant targets.

The modeling framework is based upon collaboration between multiple software agents. For CISAT agents, the environment is the problem space, and they sense it by evaluating potential solutions. Agents then respond by creating, sharing, and refining solution concepts. Within CISAT, every human designer is modeled by exactly one agent. These agents share a common goal (the minimization of an objective function) making them a suitable proxy for members of a team (Figure 7). The agents search based on a simulated annealing algorithm, modified by the above characteristics.

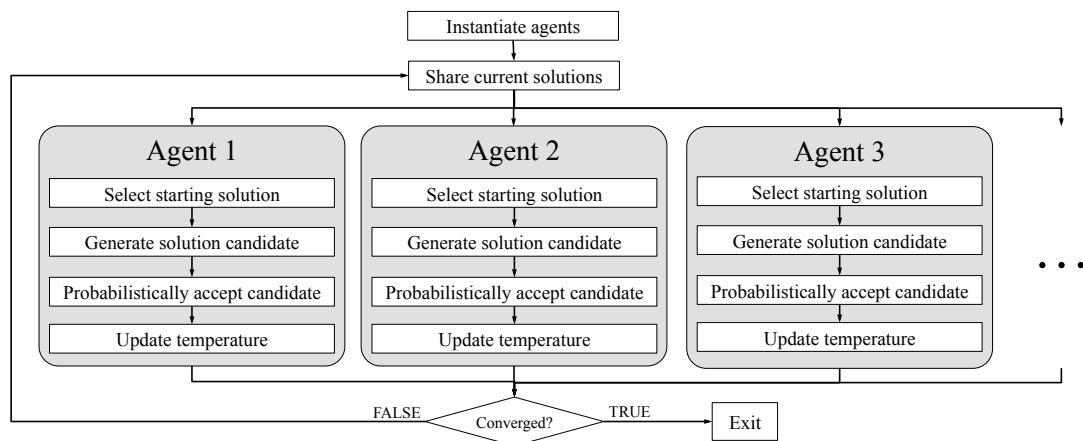
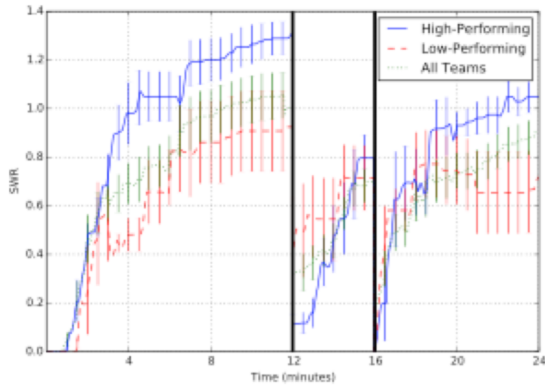
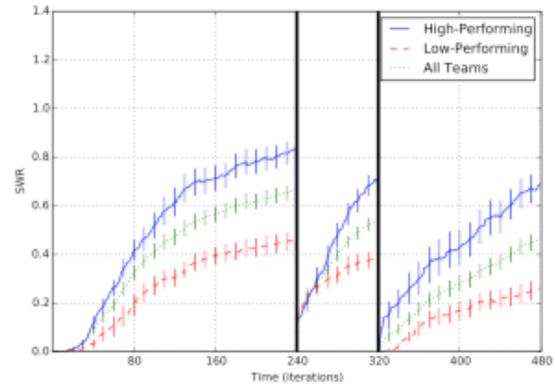


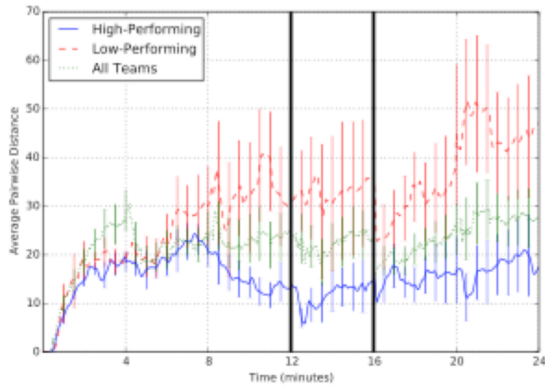
FIGURE 7. Conceptual flowchart for CISAT framework



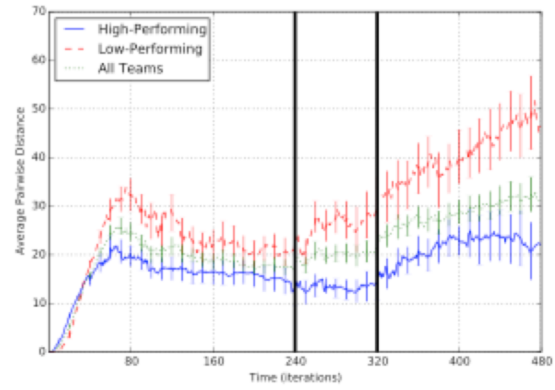
(a) SWR of best design
(cognitive study results)



(b) SWR of best design
(CISAT simulation results)



(c) Average pairwise distance
(Cognitive study results)



(d) Average pairwise distance
(CISAT simulation results)

FIGURE 8. Comparison between cognitive study results and CISAT simulation results

The CISAT framework reproduces several of the main trends that are apparent in the original results from the cognitive study. Among other similarities, the high-performing human teams showed an early divergent period, followed by a pattern of fairly constant average pairwise distance (see Figure 8c). This is echoed in the CISAT simulation (see Figure 8d). The low-performing human teams show higher average pairwise distance, and a period of divergence near the end of the study. This behavior is also evidenced in the CISAT simulation. As seen in Figure 8 a&b, even the overall trends for the calculation of the design goals (SWR – strength to weight ratio) is consistent although the actual values are slightly lower in the simulation.

CISAT was used to explore the particular characteristics that were most beneficial to teams in solving this task. This analysis indicated that proper interaction (specifically self-bias and organic interaction timing) was crucial to enabling team success in the truss design task. Further analysis revealed the importance of flexible design methods that allow for sufficient, but not excessive, divergent search.

STUDY 4: Using CISAT as the basis for effective numerical optimization (McComb, Cagan and Kotovsky, 2015c & 2015d)

This CISAT work provides the basis for a novel and effective optimization method. Called the Heterogeneous Simulated Annealing Team (HSAT) algorithm, this multi-agent simulated annealing algorithm includes multiple agents that each provide their own adaptive annealing schedule, allowing agents to develop heterogeneous search strategies. Such diversity, appropriately delimited, is a natural part of engineering design, and also boosts performance in other multi-agent design algorithms. Further, interaction between agents in HSAT is structured to mimic interaction between members of a design team as derived in Study 3 above. The performance of this new algorithm is compared to several other simulated annealing based algorithms, as well as a random search algorithm, a gradient-based algorithm, and a genetic algorithm. Although the HSAT algorithm tends to display slow initial improvement, it provides terminal solutions that are better on average than other algorithms explored in this work.

A general flowchart is provided in Figure 9 to summarize the HSAT algorithm.

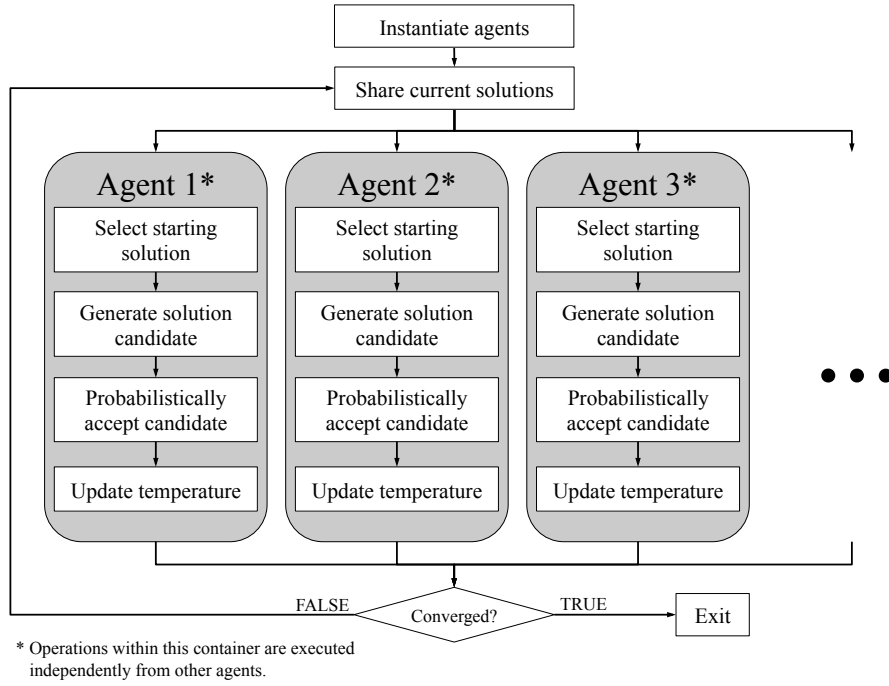
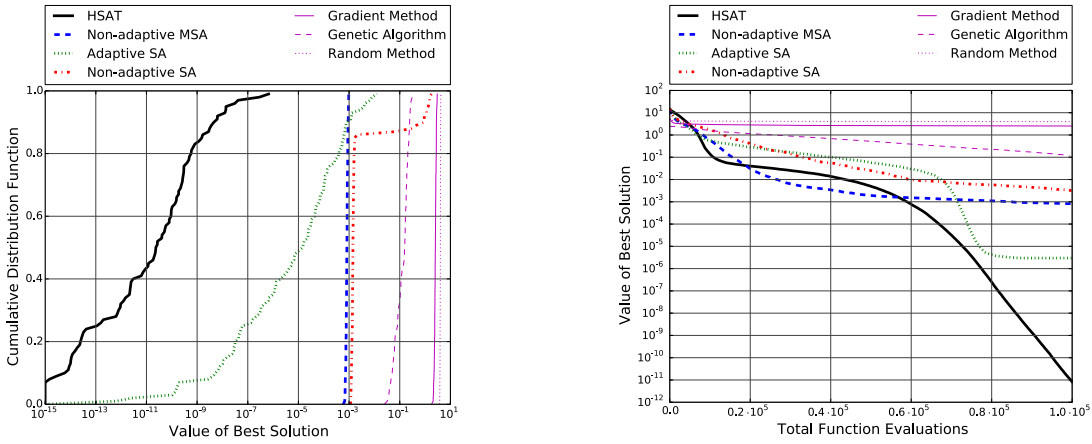


FIGURE 9. Flowchart for the HSAT algorithm.



(a) Cumulative distribution of terminal solution (b) Best solution found over time.

FIGURE 10. Comparison of optimization results for Ackley function.

The algorithm has been applied to several objective functions of multiple minima.

The results in comparison to a variety of other optimization methods are shown in Figure

10 for the Ackley function. (In Figure 10a higher values are better and in Figure 10b lower values are better.) Most impressive in this instance is HSAT's ability to go beyond the other algorithms to find a much better solution.

STUDY 5: Overcoming fixation in misleading situations through interruption (Sio, Kotovsky and Cagan, 2014a)

Many studies investigating the unconscious processing that lead to insight assume that incubation and subsequent insight experiences begin with an impasse. Our study challenges this assumption. Participants were asked to solve a set of remote associate tasks in two test sessions, with or without incubation in between. Half of the tasks were designed to activate a misleading solution attempt whereas the others were neutral. The degree of impasse was manipulated by presenting the tasks for one long time each or briefly for multiple times (with total time kept equivalent) intermixing the two tasks with each other. The multiple-presentation group should be less likely to reach an impasse because they could only approach the problem briefly each time. However, this group performed as well as the single-presentation group on the neutral tasks and solved *more* misleading tasks than the single-presentation group. Both groups benefited from incubation. We conclude that unconscious insight-related processes are not impasse-driven and prolonged conscious work may induce fixation.

In this study, participants were asked to solve neutral and misleading RAT problems presented in a massed (30sx1) or spaced (10sx3) manner, with or without incubation. In the first session, the 10sx3 and 30sx1 groups solved the same amount of neutral RAT problems, and the 10sx3 group solved more misleading RAT problems than did the 30sx1 group. Both groups showed a significant and comparable incubation effect (30sx1: $d = .61$; 10sx3: $d = .68$). The non-significant 10sx3 vs. 30sx1 differences for the initial performance on neutral RAT and the incubation effect size suggest that reaching an impasse or not during the initial problem-solving phrase has no effect on insight, a result strengthened by the finding of increased solution of misleading problems by the 10sx3 groups.

We revealed a lack of impact of impasse on insight. We suggest that the role of the initial problem-solving attempt is for successful encoding, rather than experiencing failure. This enables individuals to maintain the task information in some non-immediate memory, providing the basis for the subsequent unconscious problem-solving processing.

STUDY 6: Meta-Analysis of design studies on example impact (Sio, Kotovsky and Cagan, 2015)

A meta-analytical review of design studies ($N = 43$) was conducted to examine the effects of examples on design processes, an issue that has been the focus of a good bit of attention. The analysis revealed that providing example solutions made individuals generate more example-related ideas and produced fewer categories of ideas, however, the ideas they generated were more novel. There was also a positive link between the degree of copying and the quality of solution ideas. The facilitatory effects on novelty and quality were stronger when fewer and less common examples were presented. Presenting a single and uncommon example may encourage individuals to shift from traversing between different parts of the problem space to conducting a deeper search in a specific and remote domain, facilitating the generation of high-quality and novel ideas.

This meta-analysis examined the effects of positive examples on design processes. The results indicate that individuals tend to copy ideas or parts of ideas from the examples and produced less variety of ideas, as compared to those who did not receive any example solution while solving the design task. The more individuals copy from the examples, the smaller number of ideas they can generate. However, looking at examples can significantly improve the quality and novelty of the solution ideas produced. These findings are consistent with our prediction that the presence of examples can modify the search strategy from a broad one to a focused one. Although this narrows the scope of search, it allows a more in-depth exploration, and in turn, improves solution quality.

Our analyses also reported a significant “timing” effect; presenting examples at the beginning of problem solving produced a larger positive impact on design solutions, as compared to presenting examples during problem solving. These results seem to be consistent with the prediction based on the sunk cost effect that after a period of initial

work on the task, individuals have developed a fixation or commitment to their own approach; and this should lower their tendency to make use of the external information to improve the current problem solving approach.

Our analysis did not uncover a strong correlation between the quantity and quality of the solution ideas ($r = .007$, $p > .20$). This challenges the common assumption among studies of brainstorming that the greater the number of ideas generated, the greater the chance of producing a good solution (Osborn, 1963). According to our meta-analysis, generating high quantity and generating high quality of ideas required different search strategies. Looking at examples led individuals to explore the problem space more narrowly and deeply, and this promoted the quality and novelty of the design solution. These findings support the use of examples in the design process because, in real-life problem solving, people usually value quality over quantity of solutions. Providing a single rather than multiple examples allows individuals to focus on fewer domains and to search deeper. An uncommon example will direct individuals to search in a less typical domain. Together, a focused search in an uncommon domain should facilitate novel conceptual combination. These support our prediction that looking at examples can impact how individuals explore the problem space, and this can potentially facilitate the design processes, depending on the number, commonality, and the timing of the presentation.

STUDY 7: An Empirical Study of Arrow's Impossibility Theorem (McComb, Goucher-Lambert, and Cagan, 2015)

The design process often requires work by teams, rather than individuals. During team-based design it is likely that situations will arise in which the members of the team have different opinions, yet a group decision must still be made. Unfortunately, Arrow's Impossibility Theorem indicates that there is no method for aggregating group preferences that will always satisfy a small number of "fair" conditions. This work seeks to identify methods of combining individual preferences that can come close to satisfying Arrow's conditions. Experiential conjoint analysis was used to obtain empirical utility

functions for drinking mug designs. A number of functions for constructing group preference were then analyzed using both randomly generated preferences and preferences derived from an experiential conjoint survey. The analysis involved checking each of Arrow's conditions, as well as computing the likelihood that a method will be susceptible to manipulation by a dishonest individual.

This work took an empirical approach to examine several methods for combining individual preferences into a group preference. Each of these methods, referred to in this work as aggregation functions, was analysed in terms of strategy-proofness and Conditional Arrow Fairness. Of the aggregation functions explored in this work, the Copeland function offers the highest probability of Conditional Arrow Fairness and the highest probability of strategy-proofness. This indicates that it is likely to return a fair result, and that individuals would thus have no incentive to provide anything but their true preference for the alternatives. This result is true for both empirical preference profiles and randomly generated preference profiles (which offer a worst-case scenario for forming a group preference). The Copeland function could be applied to a variety of domains, including the aggregation of preferences from user surveys and decision-making during the design process.

HIGHLIGHTS OF RESULTS

The studies to date, while covering a wide variety of issues and using both computational modelling and human experimental investigations, have provided some converging findings about factors that determine the efficacy of team problem solving. These include the following:

1. The structure of teams wherein heterogeneous teams produced better outcomes and were better able to respond to changes in the problem being worked on. This finding emerged from both the human and computational studies and to some extent was based on the minimization of self bias among team members.

2. Despite the above findings about the advantages of heterogeneous teams, which suggests variability as a desirable feature of problem solving, the findings from both human and computational modelling show that the more efficacious teams explore much more efficiently than less efficacious teams. They do search broadly briefly but then narrow their search of and focus more deeply in the problem space (albeit in better or more propitious directions, similar to expert problem solvers in other domains.) Further they are better able to recover from sudden changes in the problems that occur as they work on them. This too was found in both human studies and our computational models.

3. Presenting problem examples to solvers was found, via a meta-analysis, to lead to more focused search (as in points one and two above) and to the recognition that the brainstorming idea that quantity of ideas always produces higher quality is not accurate. As in point two, narrower more focused search produced better outcomes and this was particularly true in the case of the presentation of unique examples.

4. Finally, the ten vs. thirty second study showed that reaching an impasse is not an important part of achieving insights; people that stopped solving and switched to another problem well before reaching a solution or an impasse do better overall than those allowed to steadily work on one problem for a longer time and then the other. It also showed that problems can be carried in an unconscious store while working on

another problem, only to re-emerge when work on the problem is re-activated, again leading to more focused and successful search for a solution. These and other of our findings suggest intriguing ways that team performance and problem solving search might be improved. One over-arching outcome of this work is the finding of value in rapidly narrowing or converging search, often after a brief initial period of broader search, much as has been found in studies of expertise, where insightful plunging ahead on a propitious pathway leads to the best and most rapidly acquired solutions. While much remains to be done, the findings to date suggest quite strongly that team structure, timing of problem-solving work, structure of communication pathways and heterogeneity of team members' background information all can converge in enhancing the performance of problem-solving teams.

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Abstract

The focus of this work is to understand impactful aspects of team functioning as they solve complex problems, and propose the means to improve the performance of teams, under changing or adversarial conditions. By analyzing the characteristic differences between high performing and low performing teams, we identified behavior that characterized and differentiated the problem solving approach of the teams especially when the problem itself changes during solving. We then derived a simulated annealing-based algorithm that mimicked human team problem solving under these conditions; aspects of the algorithm also performed well as an optimization algorithm when solving a variety of hard numerical problems. Identification of the impact of team structure on problem solving behavior under changing conditions indicates that heterogeneous-grouped teams outperform homogeneous or non-grouped teams. Yet solving multiple problems sequentially is not as effective as breaking problems into smaller intermixed chunks, breaking fixation. Finally, a meta-analysis on the design literature where the impact of examples on problem solving was studied within the design process identified

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